Misc.

- Plagiarism (Zero Tolerance)
  - First time 0 credit, plus half a grade penalty, will be reported to the Dean
  - Second time F grade, subject to expulsion
- What is “interpreting data”?
  - Are the statistics enough?
  - -0.5 without interpretation
- What is a “report”? Not code itself, neat, self-explanatory
- Guest lectures
  - My PhD student(s) while I am away

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Homework #2

- In the textbook (3rd Edition):
  - 2.3, 2.6, 2.7, 2.8
  - 3.1, 3.3, 3.5, 3.7, 3.11, 3.13 [MUST be done in a programming language - pseudo code does NOT count]
- Due: 9/26 11:59pm (late penalty will be enforced, 10% per day, up to 50%)

2

2

Misc.

- Recommend Reference Book
  - Social Media Modeling and Computing (Springer)
  - Representative work
- Jiawei Han
  - A collaborator on multimedia mining
  - Other connections

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Data Mining:

Concepts and Techniques

(3rd ed.)

— Chapter 3 —

Jiawei Han, Micheline Kamber, and Jian Pei

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Chapter 3: Data Preprocessing

- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
- Data Integration
- Data Reduction
- Data Transformation and Data Discretization
- Summary

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Data Quality: Why Preprocess the Data?

- Measures for **data quality**: A *multidimensional* view
  - Accuracy: correct or wrong, accurate or not, corrupted
  - Completeness: not recorded, unavailable, *disguised…*
  - Consistency: some modified but some not, dangling, …
  - Timeliness: timely update?
  - Believability: how trustable the data are?
  - Interpretability: how easily can the data be understood? are codes known?
  - *Bias? DAF’s famous statement – is bigger always better?*

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Major Tasks in Data Preprocessing

- **Data cleaning**
  - Fill in missing values, smooth noisy data, identify or remove outliers, and resolve inconsistencies
- **Data integration**
  - Integration of multiple databases, data cubes, features, or files
- **Data reduction**
  - Dimensionality reduction: PCA, subset, constructed/derivative
  - Numerosity reduction: linear/log-linear regression, histograms
  - Data compression: for transmission/storage (lossless/lossy)
- **Data transformation and data discretization**
  - Normalization: distance becomes comparable
  - Concept hierarchy generation: raw values -> range -> concept levels

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Data Cleaning

- Data in the Real World Is 'Dirty': Lots of potentially incorrect data, e.g., instrument faulty, human or computer error, transmission error
  - incomplete: lacking attribute values, lacking certain attributes of interest, or containing only aggregate data
    - e.g., *Occupation*=" " (missing data)
  - noisy: containing noise, errors, or outliers
    - e.g., *Salary*="−10" (an error, or a flag)
  - inconsistent: containing discrepancies in codes or names, e.g.,
    - *Age*="42", *Birthday*="03/07/2010"
    - Was rating "1, 2, 3", now rating "A, B, C"
    - discrepancy between duplicate records
  - Intentional (e.g., *disguised missing* data)
    - Jan. 1 as everyone's birthday?

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Incomplete (Missing) Data

- Data is not always available
  - E.g., many tuples have no recorded values for several attributes, such as customer income in sales data
- Missing data may be due to
  - equipment malfunction
  - inconsistent with other recorded data and thus deleted
  - data not entered due to misunderstanding/not in time
  - certain data may not be considered important at the time of entry
  - no register history or changes of the data
- Missing data *may* need to be inferred*

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How to Handle Missing Data?

- Ignore the tuple: usually done when class label is missing (when doing classification)—not effective when the % of missing values per attribute varies considerably
- Fill in the missing value manually: tedious + infeasible?
- Fill in it automatically with
  - a global constant : e.g., "unknown", a new class?!
  - the attribute mean
  - the attribute mean for all samples belonging to the same class: smarter
  - the most probable value: inference-based such as Bayesian formula or decision tree (or matrix completion)

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Noisy Data

- Noise: random error or variance in a measured variable
- Incorrect attribute values may be due to
  - faulty data collection instruments
  - data entry problems
  - data transmission problems
  - technology limitation
  - inconsistency in naming convention
- Other data problems which require data cleaning
  - duplicate records
  - incomplete data
  - inconsistent data

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How to Handle *Noisy* Data?

- Binning
  - first sort data and partition into (equal-frequency) bins
  - then one can smooth by bin means, smooth by bin median, smooth by bin boundaries, etc.
- Regression
  - smooth by fitting the data into regression functions
- Clustering
  - detect and remove outliers: how about *median filtering*?
- Combined computer and human inspection
  - detect suspicious values and check by human (e.g., deal with possible outliers)
- Exploit (correlation) multiple domains: feature space, sample space, *bi-lateral filtering (e.g., image noise)*

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Data Cleaning as a Process

- Data discrepancy detection
  - Use metadata (e.g., domain, range, dependency, distribution)
  - Check *field overloading* (e.g., hidden use for different purpose, LSB)
  - Check *uniqueness* rule, consecutive rule (e.g. check numbers) and null rule (e.g. special characters/values)
  - Use commercial tools
    - Data scrubbing: use simple domain knowledge (e.g., postal code, spelling-check) to detect errors and make corrections
    - Data auditing: by analyzing data to d
      to detect violators (e.g., correlation a
- Data migration and integration
  - Data migration tools: allow transformatic
  - ETL (Extraction/Transformation/Loading) transformations through a graphical user
- Integration of the above two processes
  - Iterative and interactive (e.g., Potter's W

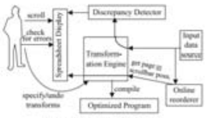

Figure 2: Potter's Wheel Architecture

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Data Integration

- **Data integration**:
  - Combines data from multiple sources into a coherent data store
- Schema integration (name conflicts): e.g., A.cust-id ≡ B.cust-#
  - Integrate metadata from different sources

Vertical
Horizontal

- Entity identification problem:
  - Identify real world entities from multiple data sources, e.g., Bill Clinton = William Clinton, grades ("S" = "P")
- Detecting and resolving data value conflicts
  - For the same real world entity, attribute values from different sources are different
  - Possible reasons: different representations, different scales, e.g., metric vs. British units

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Handling Redundancy in Data Integration

- Redundant data occur often when integration of multiple databases
  - *Object identification*: The same attribute or object may have different names in different databases
  - *Derivable data:* One attribute may be a "*derived*" attribute in another table, e.g., annual revenue
- Redundant attributes may be detected by *correlation analysis* and *covariance analysis* (how?)
- Careful integration of the data from multiple sources may help reduce/avoid redundancies and inconsistencies and improve mining speed and quality

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Correlation Analysis (Nominal Data)

- **X^2 (chi-square) test**

$$\chi^2 = \sum \frac{(Observed - Expected)^2}{Expected}$$

- The larger the X^2 value, the more likely the variables are related (the null hypothesis – unrelated - is not true)
- The cells that contribute the most to the X^2 value are those whose actual count is very different from the expected count
- Correlation does not imply causality
  - # of hospitals and # of car-theft in a city are correlated
  - Both are causally linked to the third variable: population

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Chi-Square Calculation: An Example

	Play chess	Not play chess	Sum (row)
Like science fiction	250(90)	200(360)	450
Not like science fiction	50(210)	1000(840)	1050
Sum(col.)	300	1200	1500

- X^2 (chi-square) calculation (numbers in parenthesis are expected counts calculated based on the data distribution in the two categories (last column)

$$\chi^2 = \frac{(250-90)^2}{90} + \frac{(50-210)^2}{210} + \frac{(200-360)^2}{360} + \frac{(1000-840)^2}{840} = 507.93$$

- It shows that like_science_fiction and play_chess are correlated in the group (need $X^2 > 10.8$ at 0.001 significance level)

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Correlation Analysis (Numeric Data)

- Correlation coefficient (also called Pearson's product moment coefficient)

$$r_{A,B} = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{(n-1)\sigma_A \sigma_B} = \frac{\sum_{i=1}^{n}(a_i b_i) - n\bar{A}\bar{B}}{(n-1)\sigma_A \sigma_B}$$

Why?

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective means of A and B, σ_A and σ_B are the respective standard deviation of A and B, and $\Sigma(a_i b_i)$ is the sum of the AB cross-product.

- If $r_{A,B} > 0$, A and B are positively correlated (A's values increase as B's). The higher, the stronger correlation.
- $r_{A,B} = 0$: independent; $r_{AB} < 0$: negatively correlated

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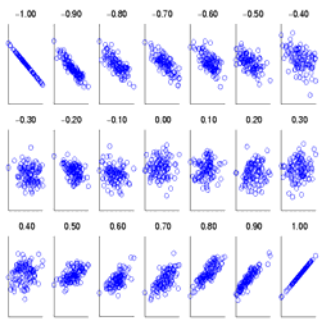
Visually Evaluating Correlation



Scatter plots showing the similarity from –1 to 1.

Note the shapes

(e.g., how poor looking 0.5 is)

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Correlation (viewed as linear relationship)

- Correlation measures the ***linear*** relationship between objects
- To compute correlation, we standardize (**why?**) data objects, A and B, and then take their dot product

$$a'_k = (a_k - mean(A)) / std(A)$$

$$b'_k = (b_k - mean(B)) / std(B)$$

$$correlation(A, B) = A' \bullet B'$$

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Covariance (Numeric Data)

- Covariance is similar to correlation

$$Cov(A,B) = E((A-\bar{A})(B-\bar{B})) = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{n}$$

Related to correlation coefficient: $r_{A,B} = \dfrac{Cov(A,B)}{\sigma_A \sigma_B}$

where n is the number of tuples, $\bar{A}$ and $\bar{B}$ are the respective mean or **expected values** of A and B, σ_A and σ_B are the respective standard deviation of A and B.

- **Positive covariance**: If $Cov_{A,B} > 0$, then A and B both tend to be larger than their expected values.
- **Negative covariance**: If $Cov_{A,B} < 0$ then if A is larger than its expected value, B is likely to be smaller than its expected value.
- **Independence**: $Cov_{A,B} = 0$ but the converse is not true:
  - Some pairs of random variables may have a covariance of 0 but are not independent. Only under some additional assumptions (e.g., the data follow multivariate normal distributions) does a covariance of 0 imply independence

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Co-Variance: An Example

$$Cov(A,B) = E((A-\bar{A})(B-\bar{B})) = \frac{\sum_{i=1}^{n}(a_i - \bar{A})(b_i - \bar{B})}{n}$$

- It can be simplified in computation as

$$Cov(A,B) = E(A \cdot B) - \bar{A}\bar{B}$$

- Suppose two stocks A and B have the following values in one week: (2, 5), (3, 8), (5, 10), (4, 11), (6, 14).
- Question: If the stocks are affected by the same industry trends, will their prices rise or fall together?
  - E(A) = (2 + 3 + 5 + 4 + 6)/ 5 = 20/5 = 4
  - E(B) = (5 + 8 + 10 + 11 + 14) /5 = 48/5 = 9.6
  - Cov(A,B) = (2×5+3×8+5×10+4×11+6×14)/5 − 4 × 9.6 = 4
- Thus, A and B rise together since Cov(A, B) > 0.

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Data Reduction Strategies

- **Data reduction**: Obtain a reduced representation of the data set that is much smaller in volume yet can produce the same (or almost the same) analytical results
- Why data reduction? — A database/data warehouse may store terabytes of data. Complex data analysis may take a very long time to run on the complete data set. Also a problem for tranmission/storage.
- Data reduction strategies
  - Dimensionality reduction, e.g., remove unimportant attributes
    - Wavelet transforms
    - Principal Components Analysis (PCA)
    - Feature subset selection, feature creation/construction
  - Numerosity reduction (some simply call it: Data Reduction)
    - Regression and Log-Linear Models
    - Histograms, clustering, sampling
    - Data cube aggregation
  - Data compression

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Data Reduction 1: Dimensionality Reduction

- **Curse of dimensionality**
  - When dimensionality increases, data becomes increasingly sparse
  - Density and distance between points, which is critical to clustering, outlier analysis, becomes less meaningful (similar to ML)
  - The possible combinations of subspaces will grow exponentially
- **Dimensionality reduction**
  - Avoid the curse of dimensionality
  - Help eliminate irrelevant features and reduce noise
  - Reduce time and space required in data mining
  - Allow easier visualization (note not in the original feature space)
- **Dimensionality reduction techniques**
  - Wavelet transforms
  - Principal Component Analysis
  - Supervised and nonlinear techniques (e.g., feature selection)

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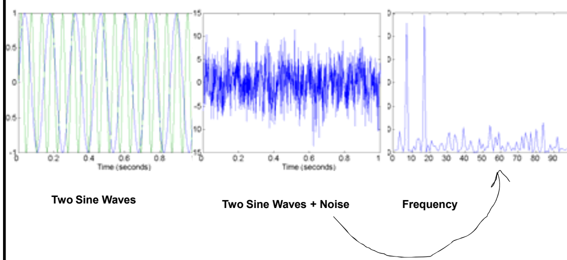
Mapping Data to a New Space

- **Fourier transform**
- **Wavelet transform**



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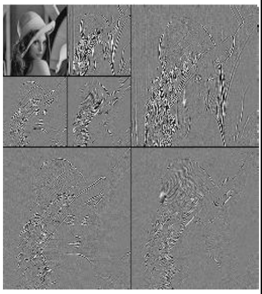
What Is Wavelet Transform?

- Decomposes a signal into different frequency subbands
  - Applicable to n-dimensional signals
- Data are transformed to preserve relative distance between objects at different levels of resolution (vs FFT)
- Allow natural clusters to become more distinguishable
- Used for image compression*



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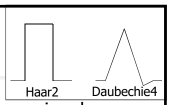
Wavelet Transformation



- Discrete **wave-let** transform (DWT) for linear signal processing, multi-resolution analysis
- Compressed approximation: store only a small fraction of the strongest of the wavelet coefficients
- Similar to discrete Fourier transform (DFT), but better lossy compression (perceptual quality, scalability), *localized* in space
- Method:
  - Length, L, must be an integer power of 2 (padding with 0's, when necessary)
  - Each transform has 2 functions: smoothing, difference
  - Applies to pairs of data, resulting in two set of data of length L/2
  - Applies two functions recursively, until reaches the desired length

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Wavelet Decomposition

- Wavelets: A math tool for space-efficient hierarchical decomposition of functions
- S = [2, 2, 0, 2, 3, 5, 4, 4] can be transformed to $S_\wedge$ = $[2^3/_4, -1^1/_4, ^1/_2, 0, 0, -1, -1, 0]$ using Haar wavelets
- Compression: many small detail coefficients can be replaced by 0's, and only the significant coefficients are retained

Resolution	Averages	Detail Coefficients
8	[2, 2, 0, 2, 3, 5, 4, 4]	
4	[2, 1, 4, 4]	[0, −1, −1, 0]
2	$[1\frac{1}{2}, 4]$	$[\frac{1}{2}, 0]$
1	$[2\frac{3}{4}]$	$[-1\frac{1}{4}]$

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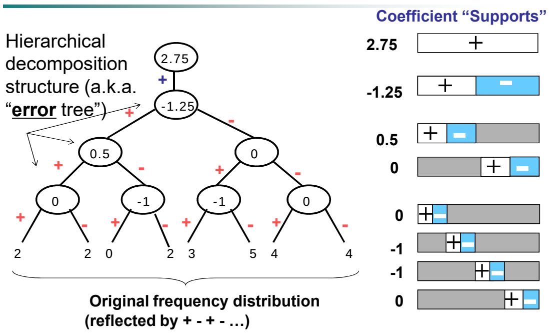
Haar Wavelet Coefficients



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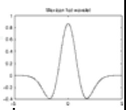
Why Wavelet Transform?



- Use hat-shape filters
  - Emphasize regions where points cluster
  - Suppress weaker information in their boundaries
- Effective removal of outliers
  - Insensitive to noise, insensitive to input order
- Multi-resolution
  - Detect arbitrary shaped clusters at different scales
- Efficient
  - Complexity O(N)
- Only applicable to low dimensional data (sequentially over the dimensions)

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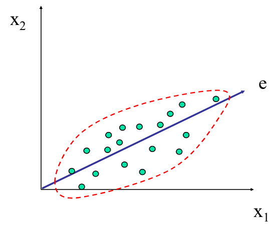
Principal Component Analysis (PCA)

- Find a projection that captures the largest amount of variation in data
- The original data are projected onto a much smaller space, resulting in dimensionality reduction. We find the **eigenvectors** of the **covariance matrix**, and these eigenvectors define the new space



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Principal Component Analysis (Steps)

- Given *N* data vectors from *n*-dimensions, find $k \le n$ orthogonal vectors (*principal components*) that can be best used to represent data
  - Normalize input data: Each attribute falls within the same range
  - Compute *k* orthonormal (unit) vectors, i.e., *principal components*
  - Each input data (vector) is a linear combination of the *k* principal component vectors
  - The principal components are sorted in order of decreasing "significance" or strength
  - Since the components are sorted, the size of the data can be reduced by eliminating the *weak components*, i.e., those with low variance (i.e., using the strongest principal components, it is possible to reconstruct a good approximation of the original data)
- Works for numeric data only

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Attribute Subset Selection

- Another way to reduce dimensionality of data
- Redundant attributes
  - Duplicate much or all of the information contained in one or more other attributes
  - E.g., purchase price of a product and the amount of sales tax paid (correlation = ?)
- Irrelevant attributes
  - Contain no information that is useful for the data mining task at hand
  - E.g., students' ID is often irrelevant to the task of predicting students' GPA

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Heuristic Search in Attribute Selection

- There are 2^d possible attribute combinations of d attributes
- Typical heuristic attribute selection methods:
  - Best single attribute under the attribute independence assumption: choose by *significance tests*
  - Best step-wise feature selection:
    - The best single-attribute is picked first
    - Then next best attribute conditioned to the first, ...
  - Step-wise attribute elimination:
    - Repeatedly eliminate the worst attribute
  - Best combined attribute selection & elimination step-wise
  - Optimal *branch and bound*:
    - Use attribute elimination and *backtracking*

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Attribute Creation (Feature Generation)

- Create new attributes (features) that can capture the important information in a data set more effectively than the original ones
- Three general methodologies
  - Attribute extraction
    - Domain-specific
  - Mapping data to new space (see: data reduction)
    - E.g., Fourier transformation, wavelet transformation, manifold approaches (not covered)
  - Attribute construction
    - Combining features (see: discriminative frequent patterns in Chapter 7)
    - Data discretization

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Data Reduction 2: Numerosity Reduction

- Reduce data volume by choosing alternative, *smaller forms* of data representation
- **Parametric methods** (e.g., regression)
  - Assume the data fits some model, estimate model parameters, store *only* the parameters, and discard the data (except possible *outliers*)
  - Ex.: Log-linear models—obtain value at a point in *m*-D space as the *product* on appropriate marginal subspaces
- **Non-parametric** methods
  - *Do not assume* models
  - Major families: histograms, clustering, sampling, …

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Parametric Data Reduction: Regression and Log-Linear Models

- **Linear regression**
  - Data modeled to fit a straight line
  - Often uses the least-square method to fit the line
- **Multiple regression**
  - Allows a response variable Y to be modeled as a linear function of multidimensional feature vector
- **Log-linear model**
  - Approximates discrete multidimensional *probability* distributions (independent or conditionally independent)
- Tools
  - SAS, Numeric Recipe

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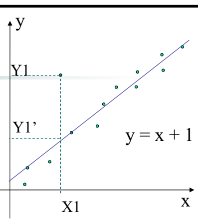
Regression Analysis



- Regression analysis: A collective name for techniques for the modeling and analysis of numerical data consisting of values of a ***dependent variable*** (also called ***response variable*** or *measurement*) and of one or more *independent variables* (aka. ***explanatory variables*** or ***predictors***)
- The parameters are estimated so as to give a "**best fit**" of the data
- Most commonly the best fit is evaluated by using the ***least squares method***, but other criteria have also been used
- Used for prediction (including forecasting of time-series data), inference, hypothesis testing, and modeling of causal relationships (*be careful!*)

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Regress Analysis and Log-Linear Models

- Linear regression: $Y = w X + b$
  - Two regression coefficients, *w* and *b*, specify the line and are to be estimated by using the data at hand
  - Using the least squares criterion to the known values of $Y_1, Y_2, \ldots, X_1, X_2, \ldots$.
- Multiple regression: $Y = b_0 + b_1 X_1 + b_2 X_2$
  - Many nonlinear functions can be transformed into the above (how?)
- Log-linear models:
  - Approximate discrete *multidimensional probability distributions (why?)*
  - Estimate the *probability* of each point (tuple) in a multi-dimensional space for a set of discretized attributes, based on a smaller subset of dimensional combinations (look for "independency")
  - Useful for dimensionality reduction and data smoothing

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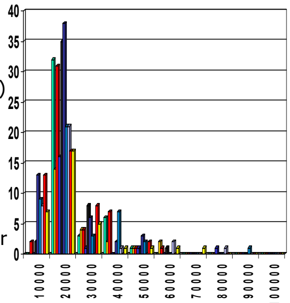
Histogram Analysis

- Divide data into buckets and store average (sum) for each bucket (good for both sparse and dense data, skewed data)
- Partitioning rules:
  - Equal-width: equal bucket range
  - Equal-frequency (roughly, or *equal-depth*) (remember *histogram equalization*?)



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Clustering

- Partition data set into clusters based on similarity, and store cluster representation (e.g., centroid and diameter) only (e.g., GMM)
- Can be very effective **if** data is *clustered* but not if data is "*smeared*" [But … still]
- Can have hierarchical clustering and be stored in multi-dimensional index tree structures
- There are many choices of clustering definitions and clustering algorithms (name one)
- Cluster analysis will be studied in depth in Chapter 10

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Sampling

- Sampling: obtaining a small sample *s* to represent the whole data set *N*
- Allow a mining algorithm to run in *complexity that is potentially sub-linear to the size of the data*
- Key principle: Choose a representative subset of the data
  - Simple random sampling may have very poor performance in the presence of skew
  - Develop adaptive sampling methods, e.g., stratified sampling:
- Note: Sampling may not reduce database I/Os (page at a time)

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Types of Sampling

- **Simple random sampling**
  - There is an equal probability of selecting any particular item
- **Sampling without replacement**
  - Once an object is selected, it is removed from the population
- **Sampling with replacement**
  - A selected object is not removed from the population
- **Stratified sampling:**
  - Partition the data set (into 'strata'), and draw samples from each partition (proportionally, i.e., approximately the same percentage of the data)
  - Used effectively in conjunction with skewed data

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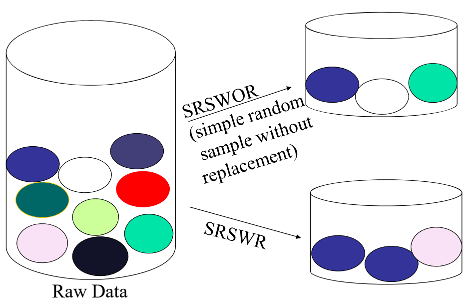
Sampling: With or without Replacement



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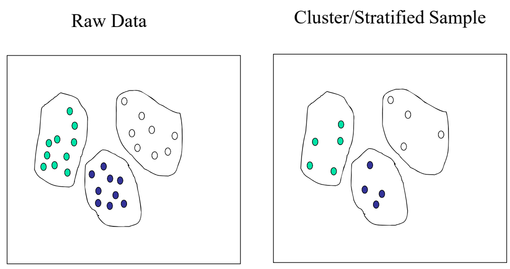
Sampling: Cluster or Stratified Sampling



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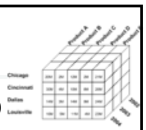
Data Cube Aggregation



- The lowest level of a data cube (base cuboid)
  - The aggregated data for an individual entity of interest
  - E.g., a customer in a phone calling data warehouse
- Multiple levels of **aggregation** in data cubes
  - Further reduce the size of data to deal with
- Reference appropriate levels
  - Use the smallest representation which is enough to solve the task
- Queries regarding aggregated information should be answered using data cube, when possible

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Data Reduction 3: Data Compression

- String compression
  - There are extensive theories and well-tuned algorithms
    - Lempel-Ziv (variable length coding), run length coding
  - Typically lossless, but only limited manipulation is possible without expansion
- Audio/video compression
  - Typically lossy compression, with *progressive* refinement
  - Sometimes small fragments of signal can be reconstructed without reconstructing the whole
- Time sequence is not audio
  - Typically short and vary slowly with time
- Dimensionality and numerosity reduction may also be considered as forms of data compression (lossy or not?)

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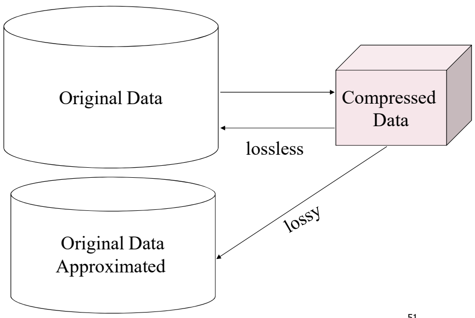
Data Compression



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- Data Preprocessing: An Overview
  - Data Quality
  - Major Tasks in Data Preprocessing
- Data Cleaning
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- Data Reduction
- Data Transformation and Data Discretization
- Summary

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Data Transformation

- A function that maps the entire set of values of a given attribute to a new set of replacement values s.t. *each old value can be identified with one of the new values (lossy or lossless?)*
- Methods
  - Smoothing: Remove noise from data (how???)
  - Attribute/feature construction
    - New attributes constructed from the given ones
  - Aggregation: Summarization, data cube construction
  - Normalization: Scaled to fall within a smaller, specified range
    - min-max normalization
    - z-score normalization (what's the difference from the above?)
    - normalization by decimal scaling (moving decimal pt. st max <1)
  - Discretization: Concept hierarchy climbing

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Normalization

- **Min-max normalization**: to [new_min_A, new_max_A]

$$v' = \frac{v - min_A}{max_A - min_A}(new\_max_A - new\_min_A) + new\_min_A$$

  - Ex. Let income range \$12,000 to \$98,000 normalized to [0.0, 1.0]. Then \$73,000 is mapped to $\frac{73,600-12,000}{98,000-12,000}(1.0-0)+0 = 0.716$
- **Z-score normalization** (μ: mean, σ: standard deviation): bounded?

$$v' = \frac{v - \mu_A}{\sigma_A}$$

  - Ex. Let μ = 54,000, σ = 16,000. Then $\frac{73,600-54,000}{16,000} = 1.225$
- **Normalization by decimal scaling**

$$v' = \frac{v}{10^j}$$ Where j is the smallest integer such that Max(|v'|) < 1

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Discretization

- Three types of attributes
  - Nominal—values from an unordered set, e.g., color, profession
  - Ordinal—values from an ordered set, e.g., military or academic rank
  - Numeric—real numbers, e.g., integer or real numbers
- Discretization: Divide the range of a continuous attribute into intervals
  - Interval labels can then be used to replace actual data values
  - Reduce data size by discretization
  - Supervised vs. unsupervised
  - Split (top-down) vs. merge (bottom-up)
  - Discretization can be performed recursively on an attribute
  - Prepare for further analysis, e.g., classification

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Data Discretization Methods

- Typical methods: All the methods can be applied *recursively*
  - Binning (replaced by mean or median of the interval)
    - Top-down split, unsupervised
  - Histogram analysis
    - Top-down split, unsupervised
  - Clustering analysis (unsupervised, top-down split or bottom-up merge)
  - Decision-tree analysis (supervised, top-down split)
  - Correlation (e.g., χ^2) analysis (unsupervised, bottom-up merge)

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Simple Discretization: Binning

- Equal-width (distance) partitioning
  - Divides the range into *N* intervals of equal size: uniform grid
  - if *A* and *B* are the lowest and highest values of the attribute, the width of intervals will be: $W = (B - A)/N$.
  - The most straightforward, but outliers may dominate presentation
  - Skewed data is not handled well (empty bins)
- Equal-depth (frequency) partitioning
  - Divides the range into *N* intervals, each containing approximately same number of samples
  - Good data scaling
  - Managing categorical attributes can be tricky

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Binning Methods for Data Smoothing

- Sorted data for price (in dollars): 4, 8, 9, 15, 21, 21, 24, 25, 26, 28, 29, 34

* Partition into equal-frequency (**equi-depth**) bins:
- Bin 1: 4, 8, 9, 15
- Bin 2: 21, 21, 24, 25
- Bin 3: 26, 28, 29, 34

* Smoothing by **bin means**:
- Bin 1: 9, 9, 9, 9
- Bin 2: 23, 23, 23, 23
- Bin 3: 29, 29, 29, 29

* Smoothing by **bin boundaries (rounding)**:
- Bin 1: 4, 4, 4, 15
- Bin 2: 21, 21, 25, 25
- Bin 3: 26, 26, 26, 34

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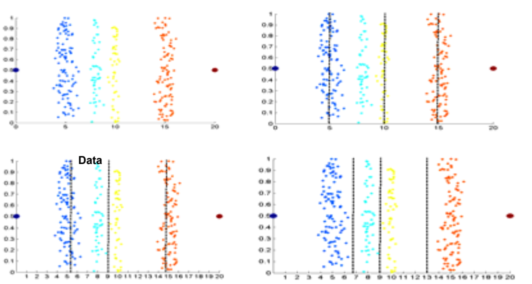
Discretization Without Using Class Labels (Binning vs. Clustering)



Equal frequency (binning)

K-means clustering leads to better results (why?)

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Discretization by Classification & Correlation Analysis

- Classification (e.g., decision tree analysis)
  - Supervised: Given class labels, e.g., cancerous vs. benign
  - Using *entropy* to determine split point (discretization point)
  - Top-down, recursive split
  - Details to be covered in Chapter 7
- Correlation analysis (e.g., Chi-merge: χ^2-based discretization)
  - Supervised: use class information
  - Bottom-up merge: find the best neighboring intervals (those having similar distributions of classes, i.e., low χ^2 values) to merge
  - Merge performed recursively, until a predefined stopping condition

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Concept Hierarchy Generation

- **Concept hierarchy** organizes concepts (i.e., attribute values) hierarchically and is usually associated with each dimension in a data warehouse
- Concept hierarchies facilitate drilling and rolling in data warehouses to view data in ***multiple granularity***
- **Concept hierarchy formation**: Recursively reduce the data by collecting and replacing low level concepts (such as numeric values for *age*) by higher level concepts (such as *youth, adult*, or *senior*)
- Concept hierarchies can be explicitly specified by *domain experts* and/or *data warehouse designers*
- Concept hierarchy can be automatically formed for both numeric and nominal data. For numeric data, use discretization methods shown.

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Concept Hierarchy Generation for Nominal Data

- Specification of a partial/total **ordering** of attributes explicitly at the schema level by users or experts
  - *street* < *city* < *state* < *country*
- Specification of a hierarchy for a set of values by explicit data **grouping**
  - {Urbana, Champaign, Chicago} < Illinois
- Specification of only a **partial set** of attributes
  - E.g., only *street* < *city*, not others
- Automatic generation of hierarchies (or **attribute** levels) by the analysis of the number of distinct values
  - E.g., for a set of attributes: {*street, city, state, country*}

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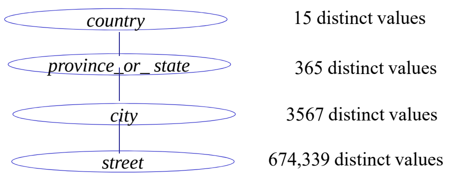
Automatic Concept Hierarchy Generation

- Some hierarchies can be automatically generated based on the analysis of the number of distinct values per attribute in the data set
  - The attribute with the most distinct values is placed at the lowest level of the hierarchy
  - *Exceptions*, e.g., weekday, month, quarter, year (it depends!)



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Chapter 3: Data Preprocessing

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HW2: Data Preprocessing

In the textbook:
2.3, 2.6, 2.7, 2.8
3.1, 3.3, 3.5, 3.7, 3.11, 3.13*

Due: 9/26 11:59pm (late penalty will be enforced)

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Summary

- **Data quality**: accuracy, completeness, consistency, timeliness, believability, interpretability
- **Data cleaning**: e.g. missing/noisy values, outliers
- **Data integration** from multiple sources:
  - Entity identification problem
  - Remove redundancies
  - Detect inconsistencies
- **Data reduction**
  - Dimensionality reduction
  - Numerosity reduction
  - Data compression
- **Data transformation and data discretization**
  - Normalization
  - Concept hierarchy generation

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Top 10 Data Mining Techniques

- 1. Regression
  2. Clustering
  3. Decision Trees/Rules
  4. Visualization
  5. k-Nearest Neighbor
  6. PCA (Principal Component Analysis)
  7. Statistics
  8. Random Forests
  9. Time series/Sequence
  10. Text Mining
- * by usage

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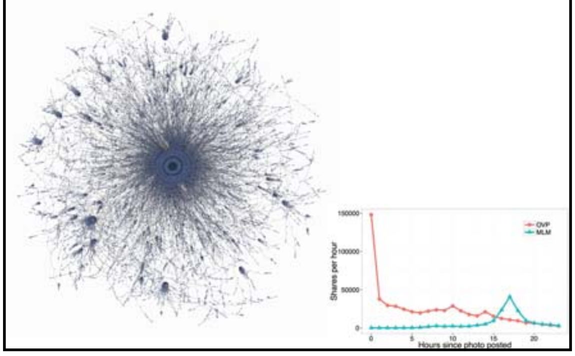
The Anatomy of Large Facebook Cascades



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